Evaluation of Cloud Prediction and Determination of Critical Relative Humidity for a Mesoscale Numerical Weather Prediction Model

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Predictions of cloud occurrence and vertical location from the Pennsylvania State University/National Center for Atmospheric Research nonhydrostatic mesoscale model were evaluated statistically using cloud observations obtained at Coffeyville, Kansas, as part of the Second International Satellite Cloud Climatology Project Regional Experiment campaign. Seventeen cases were selected for simulation during a November-December 1991 field study. MM5 was used to produce two sets of simulations, one with and one without 36-km four-dimensional data assimilation (FDDA), and a set of 12-km simulations without FDDA, but nested within the 36-km FDDA runs. The 36-km runs had 20 layers and the 12-km runs had 25 layers in the vertical direction. The 36km simulation with (without) FDDA will be designated as CNTL (CFDA), while the 12-km simulation will be referred to as FGM. Validation data were obtained from the PSU 94-GHz cloud radar.

The comparison study of the bias score (Bs), threat score (Ts), and categorized forecast (α) described by Guo (1994) for all cases shows that cloudiness is predicted well in the low and middle layers and that FDDA improves the skill of the cloud prediction in the 36-km simulations (Table 1). The 12-km fine mesh simulations, with no FDDA, but using boundary conditions from the 36-km FDDA simulations, have skill very similar to the 36-km FDDA runs. Overall, however, the standard relative-humidity-dependent cloud diagnosis in MM5 (Benjamin 1983) is found to produce a non-negligible bias that over-forecasts cloudiness in the low and high layers, particularly for the 12-km simulations. For example, Figure 1 shows that all three experiments have a strong positive bias for low clouds, such that a bias score of 1.0 (perfect) is associated with relative humidities of 83% -87%.

Table 1 . MM5 diagnosed skill scores for clouds using the standard RH _c (Benjamin 1983).				
	Skill Scores			
Low Cloud	Bs	Ts	α	
CNTL	1.30	0.54	0.68	
CFDA	1.40	0.58	0.70	
FGM	1.50	0.58	0.69	
Middle Cloud	Bs	Ts	α	
CNTL	0.85	0.48	0.71	
FGM	0.95	0.52	0.73	
High Cloud	Bs	Ts	α	
CNTL	1.19	0.42	0.53	
CFDA	1.09	0.43	0.56	
FGM	1.14	0.44	0.56	
	Standard RH _c (with respect to water)			
	Low Cloud	Middle Cloud	High Cloud	
CNTL	75%	75%	60%	
CFDA	75%	75%	60%	
FGM	75%	75%	60%	

These errors in forecasted cloud can be attributed to an improper specification of the critical relative humidity (RH_c) used to parameterize cloud occurrence in this model at these resolutions. In the original MM5, RH_c is not a function of grid scale. Results verify the hypothesis that, for mesoscale applications, RH_c should be defined as a function of model grid resolution, with higher values of RH_c used for finer resolution. New functional (optimal)

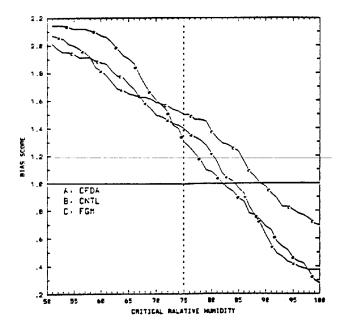


Figure 1. Evaluation of bias scores for low clouds at Coffeyville (all cases) based on standard critical relative humidity, Curve A = exp. CFDA; Curve B = exp. CNTL; Curve C = exp. FGM. Vertical dashed line is standard RH $_{\rm c}$ = 75%, horizontal line is perfect score = 1.0.

relationships are determined for both 36-km and 12-km grids (compare Tables 1 and 2) and sensitivity analysis shows improved predictive skill for clouds in MM5. For example, Figure 2 indicates that the bias score remains consistently close to 1.0 for all levels in an evaluation that groups the output into eleven validation layers (data are not applicable above 9 km in the stratosphere). Finally, analysis shows that the model predictions of cloud fields have a greater correlation with the radar-observed clouds

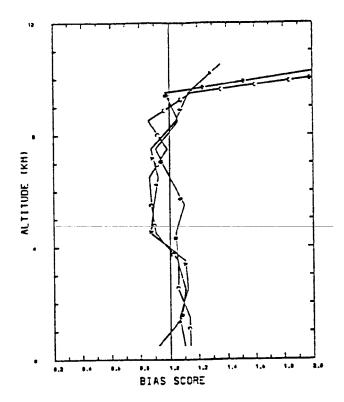


Figure 2. Bias score as a function of height calculated from 11-layer optimized values of critical relative humidity, RH_c , Curve A = exp. CFDA; Curve B = exp. CNTL; Curve C = exp. FGM. Vertical line is perfect score = 1.0.

(assumed to have very high quality) than do the Real-Time Nephanalysis (RTNEPH) cloud fields from the U.S. Air Force for the same period (Table 2). That is, the optimized MM5 has higher skill than RTNEPH for low, middle, and high clouds.

Table 2 . Optimized MM5 diagnostic skill scores for clouds.				
	Skill Scores			
Low Cloud	Bs	Ts	α	
CNTL	0.96	0.58	0.76	
CFDA	1.04	0.59	0.76	
FGM	1.00	0.58	0.75	
RTNEPH	0.72	0.55	0.76	
Middle Cloud	Bs	Ts	α	
CNTL	0.99	0.51	0.72	
CFDA	1.00	0.52	0.72	
FGM	1.03	0.55	0.74	
RTNEPH	1.14	0.45	0.62	
High Cloud	Bs	Ts	α	
CNRL	1.02	0.41	0.55	
CFDA	0.96	0.44	0.60	
FGM	1.05	0.43	0.57	

0.84

Low Cloud

83%

83%

89%

0.34

Standard RH_c (with respect r=to water)

Middle Cloud

71%

71%

72%

0.52

High Cloud

65%

65%

RTNEPH

CNTL

CFDA

FGM

References

Benjamin, S. G. 1983. Some effects of surface heating and topography on the regional severe storm environment. Ph.D. Thesis, Pennsylvania State University, 265 pp.

Guo, Z. 1994. Evaluation of cloud prediction and determination of critical relative humidity for a mesoscale numerical weather prediction model. M.S. Thesis, The Pennsylvania State University, 132 pp. (available from Department of Meteorology).